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Multidisciplinary optimization of auto-body lightweight design using modified particle swarm optimizer

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1. Abstract
Rising complexity of the automotive industry results in enormously increasing of disciplines. It becomes highly important to find the best compromise among these disciplines in the automotive design process. The coupling strategy among different disciplines and the algorithms employed to solve optimization problems are two core aspects defined by the architecture of multidisciplinary design optimization (MDO). In this paper, a MDO architecture is investigated to decide the best compromise among multiple working conditions (frontal impact, frontal offset impact, lateral impact, rear impact, auto-body stiffness and mode cases) with respect to auto-body lightweight design. Since the selection of optimization algorithms has a significant influence on the optimization time and the final solution, particle swarm optimization (PSO) algorithm is modified and promoted to accommodate different load cases. The established MDO architecture is applied to a lightweight design application of an auto-body, and the results verify its effectiveness and validity.
2. Keywords: Multidisciplinary design optimization; Particle swarm optimization; Collaborative optimization; Auto-body lightweight design; Kriging modeling technique.

3. Introduction
Because of rising complexity of industrial development, the number of disciplines to be concerned in automotive design has been increased enormously. The different disciplines, such as multiple crash cases, NVH and so on, often have conflicting objectives. So appropriate design strategies which provide an opportunity to integrate each discipline and conduct compromise searching process are required instead of solving each discipline separately [1]. Hence, multidisciplinary design optimization (MDO) has been investigated and introduced to achieve the best compromise solution.

MDO aims to utilize the couplings among different disciplines to search the global optimal design [2], and has been applied in many engineering systems, such as bridges [3], buildings [4,5], automobiles [6,7], ships [8,9] and so on. The coupling strategy of different disciplines and the algorithms employed to solve an optimization problem are two core aspects defined by the MDO architecture which significantly influence the solution time and optimal searching efficiency [10]. With respect to the auto-body design process, the traditional gradient-based methods or local search strategies are unsuitable for solving multidisciplinary optimization due to the multimodal character of the objective and the numerical noise encountered in the crash cases [1]. So global optimization algorithms should be introduced into the MDO optimization procedure. Particle swarm optimization (PSO), proposed by Kennedy and Eberhart [11], is a global optimization algorithm. Its principle is derived from the cooperative behavior appeared among species like birds, fishes etc. Because of its simplicity of implementation and strong capacity to quickly find a reasonably satisfactory solution, the PSO algorithm is becoming very popular and has been widely used. However, PSO suffers from premature convergence problem because of the quick loss of diversity in the solution search. In this research, the basic PSO is modified by OLHD technique and a reset operator to enhance the diversity among particles.

In this paper, multiple working conditions (frontal impact, frontal offset impact, lateral impact, rear impact, auto-body stiffness and mode cases) are taken into consideration. Krging modeling technique is employed to surrogate the time consuming finite element simulation. A MDO architecture based on Collaborative Optimization (CO) method is established so that each sub-system can control its own design variables and is only bounded by its own corresponding constraints. Then, with the purpose of improving the efficiency and accuracy of the optimization problem, PSO optimizer is applied and modified according to the property of each discipline. The rest of this paper is organized as follows: in Section 4, the technical base is described. In Section 5, the MDO architecture for the auto-body design is presented in detail. The lightweight design process of a car model is depicted in Section 6 and Section 7 is the conclusions of our work.

4. Technical base

4.1. Collaborative Optimization

Collaborative optimization (CO), initially developed by Braun [12], is a discipline feasible constraint method whose architecture is designed to improve disciplinary autonomy while satisfying interdisciplinary compatibility. The problem is decomposed into disciplinary sub problems sketched in Figure 1. Each sub-discipline controls its own design variables and is bounded by its own specific constraints. Interdisciplinary compatibility is the objective of each sub-discipline optimizer. At the system-level, an optimizer is employed to coordinate the whole process and optimizes the overall objective.

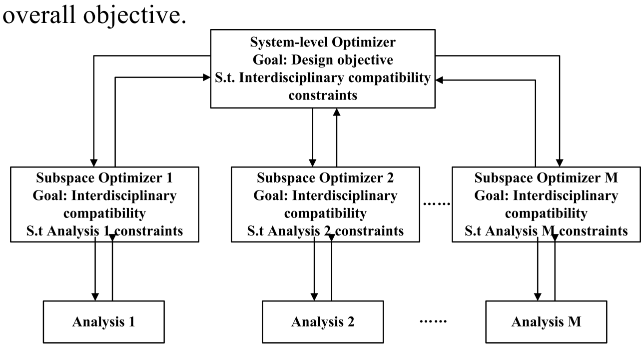


Figure 1: Collaborative optimization

4.2. Particle swarm optimization

The PSO method maintains a population of candidate solutions located in the design space of the fitness/cost function. Each potential solution is called particle and the entire population of candidate solutions is called swarm. Fitness function values of all the particles are computed in the current positions. Each particle abides two rules, trying to return to its previous best location as well as pursuing the best position of its group. The positions of particles are updated iteratively based on the algorithm. Based on the rules, the particle swarm moves like a group. The overall behavior prompts all particles to go forward the optimal solutions of the fitness/cost function.

In the standard Particle swarm optimization, consuming a problem with D-dimensions, a potential solution is expressed as the velocity and position of a particle. Vector x_k^i stands for the position of the i^{th} particle while vector v_k^i is the velocity. p_k^i represents the best previously visited position of each particle and p_k^g is the global best position found by particle swarm. The whole swarm is controlled by equations (1) and (2).

$$v_{k+1}^i = \omega v_k^i + c_1 \cdot r_1 \cdot (p_k^i - x_k^i) + c_2 \cdot r_2 \cdot (p_k^g - x_k^i) \tag{1}$$

$$x_{k+1}^i = x_k^i + v_{k+1}^i \tag{2}$$

$$\omega(iter) = \frac{(iter_{\max} - iter)}{iter_{\max}} \times (\omega_{\max} - \omega_{\min}) + \omega_{\min} \tag{3}$$

Equation (1) is the velocity update equation. Its first part is the initial velocity with inertia factor ω which provides momentum for particles to move across the design space [13]. Shi and Eberhart have proposed a linearly varying inertia weight which had a significant improvement in the performance of standard PSO [14], shown as equation (3), in which $iter$ represents the current generation and $iter_{\max}$ is the maximum generation. The second part of equation (1) is the cognition component represents the personal behavior of a particle and encourages each particle to move toward its own best previous position. The third part is called the social component which stands for cooperation behavior among particles [15]. The social component always pulls the particles moving forward the global best position. c_1 is named as cognitive scaling parameter and c_2 is the social scaling parameter [16]. r_1 and r_2 are two uniformly distributed random numbers within the range [0,1].

4.3. Metamodels construction

Metamodeling techniques are widely used to construct surrogate models, since simulation of automotive finite element models are computationally expensive [17,18]. The Kriging model [19] is employed in this research. The stochastic process is used in Kriging model for predicting the values of unknown points. Sample points are interpolated to estimate the trend of the stochastic process by Gaussian random function. The model has been proved applicable to represent the multimodal and nonlinear functions. The accuracy of the metamodels with respect to finite element models is essential for response prediction. The generally used R^2 is verified in this research. The objective-oriented sequential sampling method is implemented to improve the precision of the constructed metamodels [20].

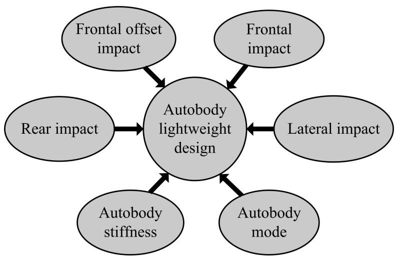
5. MDO architecture for the auto-body lightweight design

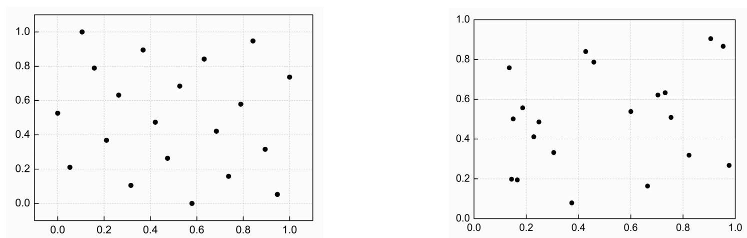
In this research, six load cases are employed (frontal impact, frontal offset impact, lateral impact, rear impact, auto-body stiffness and auto-body mode conditions shown in Figure 2) to conduct lightweight design of autobody. This Section has two parts. The first describes the modified PSO algorithm and the established MDO architecture is presented in the second part.

5.1. Modified PSO algorithm

In order to ensure a full coverage of the design space, the OLHD technique [21] is used to generate the first generation of particle swarm instead of the uniformly random distributed method (labeled as PSO optimizer version 2). In order to make a distinct comparison, particles are generated in two-dimensional space by the traditional method and OLHD technique, shown in Figure 3. It is clearly found that the distribution of particles generated by OLHD technique in Figure 3(b) is more reasonable than the random method in Figure 3(a).

From the observation of the mathematical experiments, the convergence rate of the PSO optimizer version 2 is slightly lower than the basic PSO in the beginning of the optimization procedure because of the scattering distribution of initial particles, but the former always finds a better solution at last. So the optimization ability of the basic PSO is successfully improved by OLHD technique.





(a) OLHD Samples (b) Random Samples

Figure 2: Load cases considered in MDO

Figure 3 Comparison of initial particles in two-dimension

Through experiments with numerical benchmarks, it has been observed that PSO quickly finds a relatively good local solution but sometimes stagnates in the local optimum for a considerable number of generations without any improvement. An adaptive reset operator worked on velocity is employed to enhance the global optimization ability of PSO (labeled as PSO optimizer version 1). When the optimization procedure is trapped into stagnation for several generations, the velocity of particles will be reset equation (5)

$$V_{reset} = \mu \cdot rw \cdot V_{rand}, \quad \mu = \frac{(iter_{\max} - iter_{current})}{iter_{\max}}, \quad rw = (rw_{\max} - rw_{\min}) * \frac{(iter_{\max} - iter_{current})}{iter_{\max}} + rw_{\min} \tag{4}$$

V_{rand} is randomly generated velocity matrix of particles under predefined range [-$V_{\max}$, $V_{\max}$]. μ is a generation correlation coefficient which is linearly decreased along with generation. $iter_{\max}$ is the max generation and $iter_{current}$ is the current generation. rw is a velocity correlation coefficient, and its concept is derived from the inertia weight factor ω of the standard PSO. Its boundary is the predefined [$rw_{\min}, rw_{\max}$]. Following the searching process, the left generation number ($iter_{\max} - iter_{current}$) is decreased and the value of μ is diminished, so that the algorithm convergence property can be guaranteed by shrinking the amplitude of V_{reset}, while rw improves the distribution of reset particles in consideration of the global and local search ability. The particles are scattered away from the stagnation position by equation (5) after the adaptive reset operator activated.

$$P_p = P_{stagnation} + V_{reset} \tag{5}$$

From the history of mathematical experiments, the reset operator will be activated when the stagnation judgment criterion and the predefined probability satisfied. It is obvious that the reset operator is active during the middle of the optimization history when the standard versions are fallen into stagnation. So the reset operator effectively assists the algorithm jumping out from stagnation and finding a better optimization solution. The amplitude of the reset process is decreased following the left generation diminished observed at the later stage of the optimization program, so that the convergence of the optimization program can be guaranteed. Compared with the modified PSO version 2, the convergence rate of this version is relatively lower, but it is more suitable for high-nonlinear and multimodal optimization problems benefitted from the diversity enhanced mechanism.

5.2. The MDO architecture

The flowchart of the auto-body optimization process is presented in Figure 4.

（1）The high-fidelity finite element models are established at the first step.

（2）Based on design of experiment methodology [21], implement a certain number of finite element analyses to provide data basis for metamodel technique.
（3）Construct metamodels by Krging technique and validate the precision of each surrogate model
（4）Sequential sampling method based on the expected improvement criterion[20] is applied to improve the accuracy of each metamodel.
（5）MDO procedure is launched after all the surrogate models have been prepared. The architecture of MDO is illustrated in Figure 5. In system-level, the objective is mass. The optimization constraints are derived from the interdisciplinary compatibility constraints and auto-body stiffness and mode cases. In consideration of the computational efficiency, the basic version of PSO is employed to search the optimal solution. There exist three sub-systems, frontal, lateral and rear impact. The frontal and frontal offset impact crash cases are included in the frontal impact system. According to the high non-linear property of the crash cases [1], the PSO optimizer version 1 abovementioned is adopted to search the optimum. The second sub-system solves the lateral impact case and the PSO optimizer version 2 mentioned in part one is used to conduct the optimization process. The third discipline is the rear impact case and the PSO optimizer version 2 is employed as the optimization algorithm.
（6）Validate the optimization solution using finite element analysis and output the verified results.

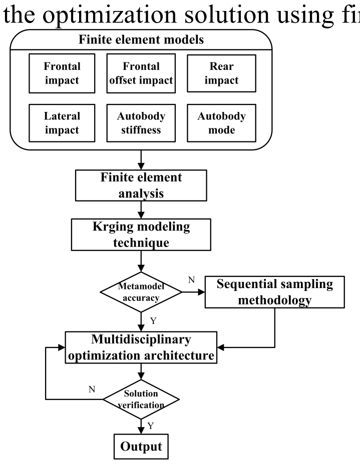


Figure 4: The flowchart of auto-body design

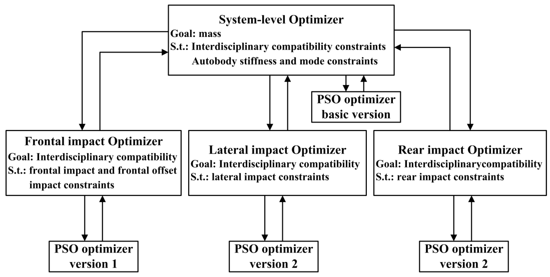


Figure 5: The MDO architecture

6. The Lightweight design of an auto-body

A B-class vehicle model is introduced in this paper illustrated in Figure 6. Strict meshing criteria are used to achieve the quality requirements so that the simulation accuracy can be promoted. The average mesh size is 10mm, while 1005019 shell elements and 22575 solid elements are contained in the full-size model. The finite element model has been verified and is available for further study [22,23]. The auto-body frame FE model are presented in Figure 7 and crash cases simulation in Figure 8.

Multi-load cases and constraints are presented in Table 1. The variable is the thickness of each component. Due to limited space, the detailed variables list is not included in this paper. For auto-body stiffness and mode cases, 90 variables are considered. Its performance indicators are served as the constraints in system optimizer so that the coupling variables can be significantly decreased to ensure the searching convergence. Because of the similar performance indicators, the frontal and frontal offset crash cases are integrated in one sub-system. The objective is the interdisciplinary compatibility and the PSO optimizer version 1 is conducted for optimal searching. 500 generations are preseted for sufficiently optimal searching. The lateral impact contains 15 variables and the PSO optimizer version 2 is employed. 300 generations are used for the optimization process. There are 8 variables in rear impact case, so the optimization searching is relatively simpler than the other two sub-systems. 100 generations are predefined with the PSO optimizer version 2. In the system-level, the basic PSO optimizer is employed and 100 generations are preseted for improving computational efficiency. The particle number is set to 20 for all the problems.

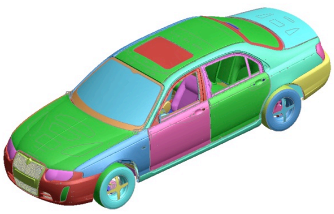


Figure 6: Full size FE model

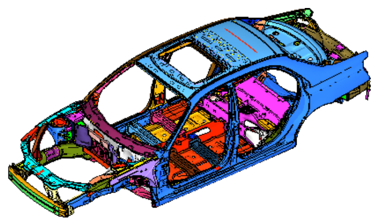
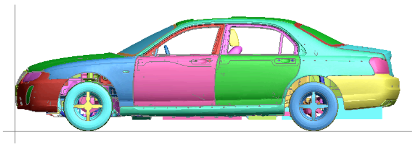


Figure 7: Auto-body frame FE model



(a) Frontal impact

(b) Frontal offset impact

(c) Lateral impact

(d) Rear impact

Figure 8 Crash cases simulation

In order to verify the efficiency and effectiveness of the modified PSO optimizer, a comparison MDO case is built with all the sub-systems optimized by basic PSO version. The predefined parameters are invariable. Because of the randomness of the results achieved by PSO, 30 repeated trials are conducted in these two MDO architecture. The best optimization result of the MDO with the modified PSO optimizer is 418.36kg, while the comparison case is 435.17kg. It is obvious that the modified PSO optimizer is efficient and effective to achieve a better optimization solution.

The original mass of the auto-body structure is 450kg. Round the thickness values of all the variables acquired from the MDO optimization procedure, and verify the feasibility by finite element analysis. The structure mass of the auto-body is 423.86kg after the lightweight design process and all the performance indicators are satisfied. So the auto-body lightweight design program based on MDO architecture and the modified PSO optimizer successfully achieve an outcome of 5.80% mass reduction.

Table 1 Load cases description

Load cases		Design variables	Performance indicators	Constraints
Auto-body stiffness		90	Bending stiffness	≥11000N/mm
			Torsion stiffness	≥12000Nm/°
Auto-body mode			First-order torsion mode	≥34Hz
Crash cases	Frontal impact	12	Left B-Pillar acceleration	≤40g
			Left Toe-board intrusion	≤80mm
			Right Toe-board intrusion	≤80mm
	Frontal offset impact	21	Left B-Pillar acceleration	≤40g
			A-Pillar deformation	≤80mm
			Left Toe-board intrusion	≤80mm
			Right Toe-board intrusion	≤80mm
	Lateral impact	15	Lower rib deflection	≤32mm
			B-Pillar intrusion velocity	≤9m/s
			Door deformation velocity	≤9m/s
			Abdomen load	≤1.5kN
			Pubic symphysis force	≤4kN
	Rear impact	8	Left contact force of Hydrogen bottle	≤50kN
			Middle contact force of Hydrogen bottle	≤50kN
			Right contact force of Hydrogen bottle	≤50kN

7. Conclusions

In this paper, MDO architecture for auto-body lightweight design is established and the modified PSO optimizer is incorporated into the optimization procedure. From the experimental results, the following conclusions can be summarized:

（1）The MDO architecture based on Collaborative Optimization guarantees the disciplinary autonomy while satisfying interdisciplinary compatibility, so that the sub-system can be operated flexibly. For the auto-body lightweight design problem, different optimization algorithms can be chosen according to the character of each sub-system

（2）The optimization ability of basic PSO is successfully improved by OLHD technique and the velocity reset operator. The MDO comparison results demonstrate that the modified PSO version is more suitable for the auto-body lightweight design.

In the future work, more load cases will be considered to incorporate into the MDO architecture while the problem convergence property is assured. More efficient PSO versions will be investigated to accommodate different requirements from multiple load cases.

8. References

[1] Fabian Duddeck, Multidisciplinary optimization of car bodies, *Structural and Multidisciplinary Optimization*, 35:375-389, 2008

[2] Sobieski I., Multidisciplinary design optimization: attempt at definition. *In: Industry university workshop on multidisciplinary aircraft design*, 23-48, 1993.

[3] Balling, R., and Rawlings, M. R., Collaborative Optimization with Disciplinary Conceptual Design, *Structural and Multidisciplinary Optimization*, 20(3), 232-241, 2000.

[4] Choudhary, R., Malkawi, A., and Papalambros, P. Y., Analytic Target Cascading in Simulation- Based Building Design, *Automation in Construction*, 14(4), 551-568, 2005.

[5] Geyer, P., Component-Oriented Decomposition for Multidisciplinary Design Optimization in Building Design, *Advanced Engineering Informatics*, 23(1), 12-31, 2009.

[6] McAllister, C. D., and Simpson, T. W., Multidisciplinary Robust Design Optimization of an Internal Combustion Engine, *Journal of Mechanical Design*, 125(1), 124-130, 2003.

[7] Kokkolaras, M., Louca, L. S., Delagrammatikas, G. J., Michelena, N. F., Filipi, Z. S., Papalambros, P. Y., Stein, J. L., and Assanis, D. N., Simulation-Based Optimal Design of Heavy Trucks by Model- Based Decomposition: An Extensive Analytical Target Cascading Case Study, *International Journal of Heavy Vehicle Systems*, 11(3/4), 403-433, 2004.

[8] Peri, D., and Campana, E. F., Multidisciplinary Design Optimization of a Naval Surface Combatant, *Journal of Ship Research*, 47(1), 1-12, 2003,.

[9] Kalavalapally, R., Penmetsa, R., and Grandhi, R., Multidisciplinary Optimization of a Lightweight Torpedo Structure Subjected to an Underwater Explosion, *Finite Elements in Analysis and Design*, 43(2), 103-111, 2006.

[10] Joaquim R.R.A. Martins, Andrew B. Lambe, Multidisciplinary Design Optimization: A Survey of Architectures, *AIAA Journal*, 51(9), 2049-2075, 2013.

[11] R. Eberhart, J. Kennedy, A new optimizer using particle swarm theory. *In: Proceedings of the Sixth International Symposium on Micro Machine and Human Science*, 39–43, 1995.

[12] Braun R, Kroo I, Development and application of the collaborative optimization architecture in a multidisciplinary design environment. *In: Multidisciplinary design optimization: state of the art.* SIAM, Philadelphia, 98–116, 1995.

[13] Y. H. Shi and R. C. Eberhart, A Modified Particle Swarm Optimizer, *IEEE International Conference on Evolutionary Computation*, ANCHORAGE, AK, 69-73,1998.

[14] Y. H. Shi and R. C. Eberhart, Empirical study of particle swarm optimization, *IEEE International Conference on Evolutionary Computation*, Washington, DC, USA, 3, 101–106, 1999.

[15] J. Kennedy, The Particle Swarm: Social Adaptation of Knowledge, *IEEE International Conference on Evolutionary Computation*, Indianapolis, Indiana, 303-308,1997.

[16] R. C. Eberhart and Y. Shi, Particle Swarm Optimization: developments, Applications and Resources, *IEEE International Conference on Evolutionary Computation*, Seoul, South Korea, 1, 81-86, 2001.

[17] Youn BD, Choi KK, Yang RJ, Gu L, Reliability-based design optimization of crashworthiness of vehicle side impact. *Structural and Multidisciplinary Optimization,* 26, 272–283, 2004.

[18] Zhang Y, Zhu P, Chen GL, Lightweight design of automotive front side rail based on robust design. *Thin Wall Struct,* 45, 670–676, 2007.

[19] Timothy, W. S., Timothy M. M., John, J. K., and Farrokh, M., Comparison of Response Surface and Kriging Models for Multidisciplinary Design Optimization, *AIAA Paper,* 98-4755, 1998.

[20] Jones D.R., Schonlau, M. and Welch, W.J., Efficient global optimization of expensive black-box functions. *Journal of Global optimization*, 13(4), 455-462,1998.

[21] Jin R, Chen W, and Sudjianto A., An Efficient Algorithm for Constructing Optimal Design of Computer Experiments. *Journal of Statistical Planning and Inference*, 134, 268-287, 2005.

[22] Siliang Zhang, Ping Zhu and Wei Chen, Crashworthiness-based lightweight design problem via new robust design method considering two sources of uncertainties., *Journal of Mechnical Engineering Science*, 0(0), 1-11, 2012.

[23] Siliang Zhang, Ping Zhu, Wei Chen and Paul Arendt, Concurrent treatment of parametric uncertainty and metamodeling uncertainty in robust design, 2013, *Structural and Multidisciplinary Optimization*, 47, 63-76, 2013.